# Visualising and minimising student academic disappointment in science courses

**Anitta Thomas[1] and André E Botha[2]**

[1]School of Computing, P.O. Box 392, University of South Africa, Pretoria, 0003

[2]Department of Physics, P.O. Box 392, University of South Africa, Pretoria, 0003

E-mail: thomaa@unisa.ac.za; bothaae@unisa.ac.za

**Abstract.** Based on existing hypotheses that correlate student satisfaction and final grades, a working hypothesis was made for Science courses: student satisfaction in a course is dependent on the similarity of their performances in various grade components. Based on this hypothesis, a new way of quantifying student disappointment was presented along with a unique visualisation to view and to facilitate interpretation of student performances and disappointments in a course. The visualisation was used to explore some of the consequences of the hypothesis using the assessment data gathered at the University of Victoria, Canada. The visualisation was further applied as a tool to assist in two example academic activities: evaluating teaching effectiveness and increasing pass rates.

## 1. Introduction

In recent years student satisfaction surveys have become increasingly popular in universities [1], because the satisfaction of students is considered one of the key indicators of the performance of a university [2]. The view of higher education as a service where the satisfaction of students is an indicator of the quality of the service provided, may have helped to solve some of the challenges universities faced; such as, high student dropout rates, decreasing student enrolment, and the allocation of public funds based on the successful completion of programmes by students [3]. However, many of these challenges remain unsolved. Hence, it is important to understand the factors that contribute to student satisfaction, or equivalently to student disappointment, and to develop the ability to assess student satisfaction accurately.

Considering all the contributing factors, student satisfaction in general is a complex concept to measure and understand [4]. In principle, a student's whole educational experience may contribute to his or her overall satisfaction with a university. However, in this paper, we make the distinction between satisfaction that is dependent on either academic or non-academic aspects of university life. We then focus on understanding aspects that contribute to a student's academic satisfaction with a course.

In the past a large number of studies, aimed at understanding the various aspects that contribute to academic satisfaction, focussed on the relationship between the final grades (expected or obtained) and the student satisfaction in the course [5-10]. This debate was already active since the early 1970s without producing consensus between the researchers regarding the reported results [10]. Due to the disparity in the results some studies explored additional aspects that could influence and explain the

correlation between final grades and student satisfaction; such as, student motivation, teaching effectiveness, classroom size, and the type of courses taken by the students [7, 9].

Studies focusing on grades as a contributing factor to student satisfaction have produced disagreeing results: some show positive correlation between grades and satisfaction [5-10], while others show insignificant or no correlation [11-12]. It is worth noting that in order to ensure anonymity, most of the aforementioned studies compared student satisfaction to the anticipated final grades, and not to the actual grades. In the study reported in [6], students were asked to complete the course survey just after their final grades were made available. The final grades were distorted in such a way that half the students obtained one grade less that their actual grade. Immediately after collecting the course surveys students were informed of their correct grades. By this method the study confirmed the idea that high grades need not necessarily result in high student satisfaction, but rather that it is the difference between the actual grade and the expected grade that is the most important contributing factor.

Guided by the idea that satisfied students are the ones whose actual grades match their expected grades, and by induction from our own teaching experience in the Sciences, we make the following working hypothesis: Students will be least disappointed in a course when they perform equally well in all grade components making up the final mark. Conversely, students will be most disappointed in courses where they perform very differently in two or more grade components. Our hypothesis may be regarded as a natural extension of the postulate made in [6], specifically adapted to the Sciences. Note that, other than grade data, it does not take into account other factors that may also contribute to student satisfaction, such as those which were mentioned in [7,9]. In a typical Science course, for example, the various 'grade components' would include the grades obtained for (i) the practical or laboratory work, (ii) assignments, (iii) a midterm examination, and (iv) the final examination.

As a first step towards testing the above hypothesis we have developed an approach to quantify student disappointment based on the differences in the marks obtained by a student in various grade components, taking into account the weight of each grade component in the final grade. We have then developed a new visualisation technique that can clearly display how students perform in the various grade components of a Science course. The visualisation is constructed in such a way as to give instructors a view of grade data which is consistent with the above hypothesis. Based on the calculated student disappointment, the visualisation is also able to indicate disappointment indices of the students.

While this study is based on the ideas from existing research on student satisfaction and grades, it differs in several ways. Firstly, unlike previous studies, the present study considers a new aspect of the important problem of understanding and accurately gauging student satisfaction. The new aspect is related to the observation that grade components in the Sciences are very different to those in the Humanities. Secondly, since student satisfaction surveys are not a measure of student learning [4], the working hypothesis that is developed in the present study may be able to provide an indication of true student learning, since it is based on performance (grade) data, rather than opinion. Unlike grade data, the data gathered from student satisfaction surveys can at best provide a measure of perceived satisfaction, which is often not related to how much learning actually took place in a course. Thirdly, a new technique to quantify student disappointment is developed based on the working hypothesis. Lastly, the visualisation technique developed here is also novel. It has been designed specifically for the Sciences in order to be consistent with our working hypothesis.

The layout of this paper is as follows. In Section 2, the technique developed for quantifying student disappointment is presented. The technical aspects of the visualisation are summarised in Section 3. A discussion on how to interpret the data in the visualisation using an ideal distribution of various grade components is included in Section 4. In Section 5, we use the visualisation to analyse real assessment data from the University of Victoria, Canada. Two of the potential applications of the visualisation are discussed in Section 6, followed by a conclusion in Section 7.

## 2. Definition of the Student Disappointment Index

Consider a class of size $n$ in which there are $m$ grade components. Assume that the grade data is contained in an array in which the $j^{th}$ grade component for the $i^{th}$ student is stored as a value between zero and one hundred in the entry $B_{ij}$. The Student Disappointment Index for the $i^{th}$ student is then defined as

$$D_i = \frac{1}{10000} \sum_{j,k=1}^{m} \left( w_j B_{ik} S(B_{ik} - B_{ij}) \right) \tag{1}$$

where $0 < w_j < 1$ is the weight of the $j^{th}$ grade component towards the final grade and $S$ is a step function which returns the value of its argument when it is positive and zero otherwise. The factor of 10000 ensures that the index is normalised to unity. The overall disappointment index for the whole class is defined as the average

$$D = \frac{1}{n} \sum_{i=1}^{n} D_i \tag{2}$$

To illustrate the meaning of the definition in (1), consider a simple case in which a certain course has only two components with $w_1=0.01$ and $w_2=0.99$. Suppose a student in this course obtains 96% for component 1 and only 3% for component 2. In this case there is only one non-zero term in the summation for the disappointment index, i.e. it is given by

$$D_i = \frac{1}{10000} \left( 0.99 \times 96 \times (96 - 3) \right) = \frac{8838.7}{10000} \approx 0.884$$

Being close to unity, the calculated value indicates that this student is highly likely to be disappointed with the course.

## 3. Basics of the Developed Visualisation

In order to visualise the working hypothesis and the student disappointment indices, we have devised a new way of plotting grade component data, using the Python programming language [13]. The script which we have written is currently compatible with data that is formatted in tab separated or comma separated format. Typically such data might be exported from learning management systems such as *Moodle* [14] or *Blackboard* [15].

After reading the data into the array $B$, the script calculates the individual and class disappointment index according to the definitions in (1) and (2). It then plots the various possible combinations of grade components against one another in a two-dimensional plot by using the transformation

$$x_i = t_i \cos\theta_i, \quad y_i = t_i \sin\theta_i, \quad \text{with } \theta_i = \frac{\pi}{4}\left( 1 + \frac{B_{ij} - B_{ik}}{100} \right) \tag{3}$$

Here $t_i$ is the final overall grade obtained by the $i^{th}$ student and $(x_i, y_i)$ are the Cartesian coordinates for the $i^{th}$ student in the plot of grade component $j$ against $k$. The Cartesian coordinates for the $i^{th}$ student is plotted as a filled coloured circle, where the colour is determined using the calculated disappointment index of the student. The developed visualisation uses colours from blue through to orange, where blue indicates the lowest possible value of disappointment of 0 (highly satisfied) and orange indicates the highest possible disappointment value of 1 (least satisfied).

## 4. Fundamental Interpretations of Plots Generated by the Developed Visualisation

Figure 1 shows an illustration of the visualisation discussed in Section 3 for ideal (fictitious) data. The radial distance from the bottom left corner to a filled circle equals the final grade of the student, while the angular separation away from the diagonal red line is the difference in grade components, as defined by $\theta_i$ in equation (3). Two visual cues are added in the grid lines: the red quarter circle indicates a final grade of 50% and the red diagonal line indicates zero difference between the marks obtained in the plotted grade components. One advantage of looking at the data in this way is that it tends to amplify the grade component differences of students with higher overall grades, while reducing the differences for students with lower overall grades. This feature of the plots is based on

our frequent observation that high performing students are generally more concerned with even minor differences in their grade component marks.

A number of elementary interpretations are valid for all the plots generated by this visualisation. All plotted circles below the red curve indicate students who failed the module. Students who have done equally well in both the grade components will appear as a filled circle on the red diagonal line. A student who performed differently in the plotted grade components appear on either above or below the red diagonal line, depending on in which grade component they did better and the angular distance from the diagonal indicates the difference in the marks obtained in the grade components plotted.
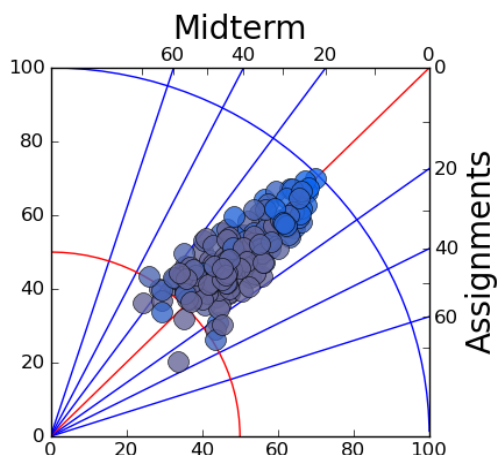


**Figure 1**: An ideal distribution of grades based on fictitious data for a class size of 157. Notice that the distribution is symmetric about the red diagonal line and, as indicated by the color of the circles, no student has a disappointment index higher than 0.5. Generally, in our experience, it is worth investigating why any student obtains a disappointment index above 0.5, since there are usually obvious reasons. The overall disappointment index for this class is 0.295.

The elementary interpretations described above can be applied to figure 1 to determine the number of students failed in the course and for comparing the general performance of students between *Midterm* and *Assignments before Midterm* grade components. It should also be noted that in figure 1, the distribution of grades occurs symmetrically about the red diagonal line, with a gradual spreading out towards the lower grades that are nearer the 50% overall mark. The symmetry of data is an ideal characteristic in such a plot because it demonstrates that on average students did equally well in both the grade components. Moreover in figure 1, the filled circles are colour coded in variations of blue and grey indicating low disappointment indices attributed to the low overall disappointment index of this class: D=0.295. The combination of symmetry about the diagonal and the low overall disappointment index makes figure 1 an ideal plot.

## 5. Analysing Plots Generated Using Real Assessment Data

Figure 2 illustrates visualisations of grade data obtained by students in various grade components of a second year Electricity and Magnetism course taught by one of the authors (AEB) at the University of Victoria in 2009. Unlike the ideal plot given in figure 1, plots in figure 2 show asymmetry of data along the diagonal red lines as well as some students with high disappointment indices, which are coloured orange.

From the plots in figure 2, it is evident that the students did not do equally well in various grade components: most students obtained higher grades for assignments than for the final exam and midterm, performed better in the practical than in assignments, and performed better in the midterm than in the final exam. In this course the grade components were not assessed at an equal standard. For example, the final exam for this course was more difficult, than the assignments students did during the term.

Due to the disparity in the marks in the various grade components the overall disappointment index is 0.375, and fifteen students have individual disappointment indices greater than 0.5. One of these students with high disappointment index (denoted with a black circle in figure 2) obtained 99, 97, 100, 98, 100, 86, 100 % for the seven assignments respectively, 87% for the practical but only received 50 and 56 % for the midterm and final exam respectively, giving him or her a final grade of 65%. This

highlighted student did equally well in the assignments and in practical but failed to perform equally well in the midterm and final exam. After the course it was discovered through student evaluations that many of the students had had access to the assignment solutions (in the form of the instructor solution manual for the textbook) and that the practical component, which had been taught by a different instructor, had been too easy.

## 6. Potential Applications

In addition to being able to view student grades and student disappointments, the visualisation can also be used as a tool to guide other academic activities in Science courses. As examples, two such activities will be considered: improving the teaching effectiveness of various grade components and adjusting grades to increase the pass rates in a course. Even though increasing pass rates is not always academically justifiable, there are times when it may be necessary. For example, it may be reasonable to normalise the current pass rates with previous years' pass rates or to normalise pass rates of various classes of the same course taught by different instructors when there were differences in the assessment standards.
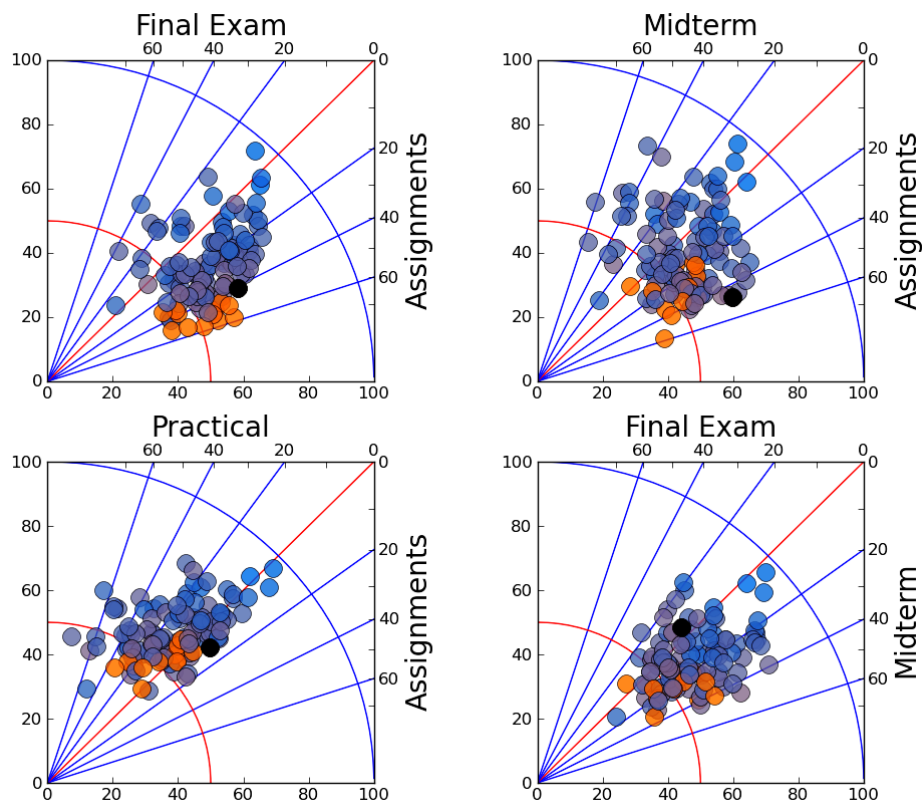


**Figure 2:** Four out of the six possible visualisations of grade data for 113 second year students who attended an Electricity and Magnetism course. The weights of the grade components were 0.10 for assignments, 0.20 for practical, 0.20 for midterm and 0.50 for the final exam. The overall disappointment index for this class is 0.375, which is higher than the ideal described in figure 1. Orange coloured circles flag students with disappointment indices greater than 0.5. One orange circle was changed to black purely for the purposes of the individual analysis given in the main text.

Based on the visualised performances of students one can more easily evaluate the effectiveness of various assessments in the respective grade components in a course. Consider a scenario where the visualisation of differences in the marks between final exam and assignments clearly demonstrates that

students performed poorly in the final examination compared to the assignments. In such a scenario one can investigate whether this difference in performances is due to the difference in the levels of difficulty of these two grade components or if the assignments did not adequately prepare students for aspects that were tested in the exam. In this respect the visualisation has the potential to be used as a tool to reflect upon teaching effectiveness.

The visualisation can also be used to increase pass rates, when there are reasonable grounds for doing so, without increasing the overall disappointment index. The increase is achieved by reducing the differences in student performance within each grade component pair. To reduce the differences systematically, a best fit polynomial curve is constructed for each plot (see black curve in figure 3). Subsequently the lowest of the two grade component marks for each student is *increased* by a small fraction of the corresponding difference between the polynomial curve and the red diagonal line. After all students have been adjusted in this way, the new best fit polynomial for the adjusted data is calculated. The area between this new polynomial and the red diagonal line is now slightly smaller than before, i.e. some of the asymmetry in the data has been removed. At the same time the student disappointment indices have been reduced and, since each student's grade has been increased in the process, there is an increase in pass rate. This process can be repeated until either the desired pass rate is achieved or else until all the asymmetry in the grade component data has been removed, i.e. until all the areas are zero.The step-by-step procedure to increase the pass rate while reducing the overall disappointment index is given in Appendix A.
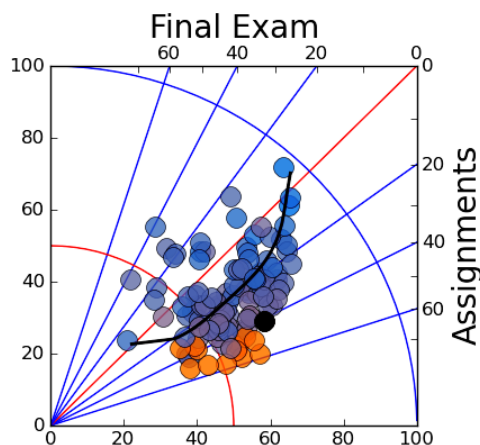


**Figure 3:** The *Final Exam* and *Assignments* plot in figure 2 is supplemented with a polynomial fit (shown by the black curve). The asymmetry in the data is now more apparent and moreover it is quantified in terms of the area between the polynomial fit and the red diagonal line.

### 7. Conclusion

To conclude, the working hypothesis made in this preliminary work has allowed us to quantify student academic disappointment and to give brief analyses of student performances in various grade components, through the use of the developed visualisation. Two examples have been provided to illustrate how the method may be used in typical academic activities within the Sciences. A study is currently underway to test the working hypothesis and the results will be published in a future article.

### Acknowledgment

**Appendix A. Step by step procedure to increase the pass rate of a class with *m* grade components**
In order to describe the procedure we first make the following definitions:

$Q$ = the number of different grade component (GC) pairs. Each pair represents one possible plot.
$I = [I_1, \ldots, I_Q]$ is a list in which each $I_i$ contains the two grades for all students in the ith GC pair.
$R$ is the red diagonal lines in each of the $Q$ plots.
$F$ is the list of final total grades.
$CP$ is the pass rate (number of students who passed/total number of students in the class)
$DP$ is the desired pass rate

| Step | Description of procedure |
|---|---|
| **1.** | Compute the list of polynomial curves $C = [C_1, \ldots, C_Q]$ to best fit the lists of data in $I$. |
| **2.** | Compute list of areas $A = [A_1, \ldots, A_Q]$, where $A_i$ represents the area between $C_i$ and $R$. |
| **3.** | Find $A_h$ = first maximum area in $A$. |
| **4.** | If $A_h$ is zero, end. |
| **5.** | Increase grades in $I_h$ by a small fraction of corresponding difference between $C_h$ and $R$. |
| **6.** | Compute pass rate $CP$ using the modified data in $I_h$. |
| **7.** | If $(CP < DP)$ and all areas are not zero then go to step 2, else end. |

**References**
[1]    Walker D J and Palmer E 2011 The relationship between student understanding, satisfaction and performance in an Australian engineering programme *Assessment abd Evaluation in Higher Education* **36** 157-70
[2]    Ansari W E and Moseley L 2011 You get what you measure: assessing and reporting student satisfaction with their health and social care educational experience *Nurse Education Today* **31** 173-8 and references therein.
[3]    Elliott KM and Shin D 2002 Student satisfaction: an alternative approach to assessing this important concept *Journal of Higher Education Policy and Management* **24** 197-209
[4]    Wiers-Jenssen J, Stensaker B and GrØgaard J B 2002 Student satisfaction: towards an empirical deconstruction of the concept *Quality in Higher Education* **8** 183-95
[5]    Feldman K A 1976 Grades and college students' evaluations of their courses and teachers *Research in Higher Education* **4** 69-111
[6]    Holmes D S 1972 Effects of grades and disconfirmed grade expectancies on students' evaluations of their instructor *Journal of Educational Psychology* **63** 130-3
[7]    Howard G S and Maxwell S E 1980 Correlation between student satisfaction and grades: a case of mistaken causation? *Journal of Educational Psychology* **72** 810-20
[8]    Pike G R 1991 The effects of background, coursework, and involvement on students' grades and satisfaction *Research in Higher Education* **32** 15-30 and references therein.
[9]    Powell R W 1977 Grades, learning, and student evaluation of instruction *Research in Higher Education* **7** 193-205 and references therein.
[10]   Scheurich V, Graham B and Drolette M 1983 Expected grades versus specific evaluations of the teacher as predictors of students' overall evaluation of the teacher *Resource in Higher Education* **19** 159-73 and references therein.
[11]   Hildebrand M, Wilson R C and Dienst E R 1971 Evaluating university teaching *Report by the Berkeley Center for Research and Development in Higher Education* (University of California, Berkeley)
[12]   Voeks V and French G M 1960 Are Student-ratings of teachers affected by grades?: Report of three studies at the university of Washington *Journal of Higher Education* **31** 330-4
[13]   Python Programming Language – Official Website. Available from http://www.python.org/.
[14]   Moodle. Available from http://moodle.org/.
[15]   Blackboard. Available from http://www.blackboard.com/.